PREDICTIVE MODELING AND CULTURAL RESOURCE PRESERVATION IN SANTA CRUZ COUNTY, ARIZONA

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By

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Abstract

The establishment of a Santa Cruz Valley National Heritage Area in southeastern Arizona presents challenges to archaeologists wishing to contribute to synthetic overviews of the region's landscape history. This paper focuses on the use of GIS and predictive modeling to provide a concise picture of prehistoric land use as manifested in the archaeological record of this region. Common quantitative methods proved useful but technical and conceptual obstacles were encountered and overcome. A view of the archaeological record as one element in a dynamic process of contemporary landscape construction altered our modeling goals. We found it necessary to reconsider standard approaches to the use of extant data sources, derivation of environmental variables, and techniques of model development. Here we present new perspectives on locational bias in archaeological data, hydrological modeling in arid regions, and statistics for selection of independent variables.

Introduction

Predictive models of archaeological site location are among the most attractive and useful strategies for professionals in the applied sector of our field, broadly referred to as cultural resource management (CRM). Using inferences from known archaeological sites and their environmental context to predict unknown site locations and to model archaeological sensitivity has become increasingly practical, and technical refinements in model development now make it relatively easy to produce models offering significant insight (e.g. Westcott and Brandon, eds. 2000). Yet, several methodological and theoretical dilemmas have inhibited the full realization of predictive modeling potential in the management context.

At the technical level, identifying, deriving and selecting variables that structured past land use remains one of the most important and problematic aspects of model development (Ebert 2000). Many environmental attributes such as water availability and terrain are known to have been critical, and abundant digital data on these is readily available. Valuable progress on techniques for deriving useful indices from these data has been made (e.g. Kvamme 1985; Warren 1990a; Duncan and Beckman 2000). However, use of some attributes is still hindered by significant differences between current and past conditions, as well as scalar discrepancies between current mapping standards and past land use.

In addition, techniques for selecting from among potential subsets of significant variables remain problematic.

At the conceptual level, the importance of predictive modeling for CRM is commonly acknowledged (e.g. papers in Sebastian and Judge, eds. 1988), but most literature on the method and theory behind it is dominated by an essentially academic goal of explaining past human behavior. Relatively little attention has been given to ways of integrating such research goals with other non-academic interests in the archaeological record. Furthermore, while the differences between CRM and academic research goals are sometimes acknowledged, relatively little attention is paid to variability within the CRM context that is also concerned with the present and future.

In our work we encountered some common technical problems and attained solutions we hope will further advance this field. On an interpretive and theoretical level we found ourselves at odds with some attitudes toward predictive modeling that affected our goals and methodological choices in ways we think merit greater discussion. Our goals in this paper are threefold, to: 1) illustrate a simple but useful model developed with readily available tools and data, 2) offer a few simple technical solutions to problems we faced, and 3) address some of the theoretical and practical implications of the varying goals of predictive modeling.

Project Description

In recent years the government of Pima County, Arizona and other organizations developed the Sonoran Desert Conservation Plan (SDCP), including a Geographic Information System (GIS) for use in planning development in the context of rapidly increasing local population. Among the many components of this system is an archaeological sensitivity map of the eastern part of the county, where most development is occurring. This map was produced by a team of local archaeologists with detailed knowledge, who manually drew maps of areas they knew to have high concentrations of cultural resources. This map was integrated with other information in the GIS to enable the county government to evaluate spatial relationships among cultural resources and other aspects of the environment affecting policy and planning.

A recent initiative to establish a National Heritage Area (NHA) in the Santa Cruz Valley prompted a renewed interest in the SDCP archaeological sensitivity map and a desire to produce something comparable for Santa Cruz County. Eastern Pima County comprises the lower (northern) portion of the Santa Cruz Valley as conceived for the NHA, and Santa Cruz County comprises the upper (southern) portion of the valley. Unlike Pima County, Santa Cruz County did not have a comparable archaeological sensitivity map. The NHA feasibility study, however, required thematic maps of the entire area as a single management entity. Given budgetary and time constraints, we were required to use existing data and available tools to produce such a map. Based on information acquired from public sources including the United States Geological Survey (USGS), the Arizona State Land Department (ASLD), and the AZSITE Arizona archaeological sites database, and using *ArcGIS* software, we developed a predictive model of archaeological sensitivity. Our GIS software was provided with significant assistance from an ESRI Conservation Grant.

An important aspect of this project was the need to produce maps of resources relevant to the specific goals of developing of the NHA. Furthermore these maps needed to provide a sense of the resources as they were integrated into a set of interpretive themes. Ten themes were described including seven with a cultural orientation. These included: Sky Islands and Desert Seas, Streams in the Desert, Bird Habitats and Migration Routes, Native American Lifeways (11,000 B.C. to present), Desert Farming (2000 B.C. to present), Ranching Traditions (1680 to present), Spanish and Mexican Frontier (1680 to 1854), Mining Booms (1680 to present), U.S. Military posts on the Mexico Border (1856 to present), and U.S. – Mexico Border Culture (1854 to present).

Of these, Native American Lifeways and Desert Farming are directly related to our modeling and are focused on prehistoric settlement and land use. Most of the themes also emphasize various aspects of life along the river oases that are so prominent in this desert environment and provide the unifying principle for the NHA. Demonstrating in a clear and concise way the archaeological aspects of this relationship between land use and the Santa Cruz River system was a key focus of the present analysis.

The larger goal of the NHA designation is to develop heritage and nature tourism in the area. Estimated impacts of increased tourism resulting from the NHA designation are approximately $1.8 billion and 40,000 new jobs over the first ten years. Given that this development is focused in large part on the cultural resources of the area, it is necessary to both illustrate where those resources are located and how they will be affected by increased activity. This goal is limited by the still unknown elements of the archaeological record.

A good deal is currently known about cultural resources in the area but more remains to be discovered and incorporated into our understanding of the region's past. For example, the importance of this area in the early development of agriculture and sedentary life in North America remained unknown until recent highway salvage work revealed deeply buried deposits in the river floodplain (e.g. Gregory 2001; Mabry 1998). Thus a model of our current knowledge of potential deposits and their relationship to likely environmental variables structuring other heritage tourism themes was a desired product to illustrate the unique and significant contribution of the Santa Cruz Valley to American heritage. We found this model served our purpose well and is an example of what can be done with commonly available data and software. In the process, however, we were confronted with a number of technical and conceptual issues that had to be addressed.

Practical and Theoretical Implications of Prediction

An essential question in discussions of predictive modeling concerns the matter of what is being predicted. Emphasis is typically on the ability of archaeologists to accurately predict and hence explain patterns in the archaeological record (Ebert and Kohler 1988). What this view undervalues is the role of predictive modeling in understanding the articulation of past and future land use, which is a vital objective in many CRM contexts and is an area in which prediction takes on a more dynamic role. It is also noted that quantitative site location studies of the type described here are more correlational than predictive (Savage 1990). This terminology holds important implications for the potential goal of modeling as it broadens our perspective to include any spatial correlation between the archaeological record and other landscape qualities of interest. In our project in Santa Cruz County we found that this shift in perspective had significant implications for model development.

A central dichotomy in different approaches to predictive modeling concerns the role of explanation. The importance of explanation may be neglected in predictive models developed in a CRM context, on the assumption that it is not necessary to understand site location decisions to effectively predict site locations and manage resources. Conversely, most argue that explanation is the primary goal of prediction and that efforts toward predictive models without explanation are misplaced (Kohler and Parker 1986, Gaffney and van Leusen 1995). Part of the problem with simple prediction is that it is perceived as a vacuous mathematical exercise in the absence of a higher purpose that justifies the expense of public funds. As Kohler and Parker (1986:42) note, “Sites are not worthwhile ends in themselves, but the understanding of human behavior and development that can be extracted from them is.”

Current historic preservation laws and regulations emphasize the importance of information potential and most CRM work is developed with an explanatory research design. The importance of information potential in CRM is supported in concept and by its prevalent use as the criterion for designating sites eligible for inclusion in the National Register of Historic Places (NRHP) in the U.S. (Sebastian and Judge 1988a). This emphasis on information and understanding is evident in most academic and CRM work and constitutes a valid goal. It does not follow, however, that this is the only valid end for archaeological predictive modeling and it is a consideration of alternative ends that emphasizes the value of alternative approaches to methodological issues (Gaffney and van Leusen 1995).

There are multiple valid interests in the archaeological record and the most effective ways to serve these are not necessarily the strict goal of explaining the past. Approaches to predictive modeling that emphasize such explanation may under-serve other interests. Lipe (1984) indicates for example, that cultural resources have four different kinds of value including informational (research), economic (market value), aesthetic (contemporary appeal) and associative (sentimental or familiar). He argues that management of resources will involve competition among interest groups emphasizing different values. Van Leusen (1995) echoes this view in a predictive modeling context, arguing that archaeological resources have economic value (as tourist attractions) and landscape value (to remind us of our roots and their time depth), in addition to scientific value (telling us something about the human past).

In the U.S., native people have a strong interest in the archaeological record that may diverge substantially from the goal of scientific explanation, and their primary reason for wanting to protect ancient sites is typically not to save them for future information gathering (see Swidler et al., eds. 1997). While such conflicts of interest are often perceived to stem from fundamentally different worldviews, similar divergences occur within the Euro-American community interested in historic preservation. To take a simple example from our region, saving the last Hohokam ballcourt from destruction would be of questionable scientific value, yet few archaeologists would dispute the merit of such a plan. A growing sense of the economic, landscape and political values of the archaeological record requires a broadened perspective on predictive modeling. From this perspective it might be argued that sites are, in fact, a worthwhile end in themselves.

Carver (1996) revisits the question of archaeological value to explore the integration of research with competing interests. He argues that ultimately all other values are derived from research that informs us about what is important or relevant about the archaeological record. We argue that this perspective is too narrowly shaped by a contemporary European context that fails to accommodate the wide variety of reasons people around the world have valued remains of the past throughout millennia. Carver does, however, make the important point that even in a research context the importance of the archaeological record is a fluid matter, dependent on current conditions and "in a state of continual redefinition" (1996:55). This flux results from social and theoretical concerns that are constantly changing and whose future is unknowable. Carver's observation is provided in support of a policy that emphasizes the still unknown aspects of the archaeological record, and the ever-changing interface between that record and equally unknown future research values.

This enlarged sense of the value of cultural resources alters the role of prediction in a number of important ways (van Leusen 1995; Dore and Wandsnider 2005). Among the requirements of modeling in this context are maps focusing on landscapes and deposits instead of sites, attention to formation processes that affect the future of resources, and the potential for rapid, large-scale iterative model development using readily available tools and data. In addition, modeling for alternative needs may affect issues such as sample selection and quantitative approaches. These requirements are not irrelevant to academic research, but the CRM context makes their practical solution a more urgent concern and may alter the cost/benefit of striving for a tenuous and problematic explanation whose value is likely temporary. Improved predictive success can be achieved through strategies that do not necessarily improve our current understanding of past cultures. In fact such understanding may be tangential to primary goals of preservation and conservation.

As part of a broader political effort, the model described here must clearly convey the richness of our record of the past and, relatively simply, a sense of how that record is integrated with other resources. These messages would not be well served by a treatise on the subtleties of site function during different periods or the complex processes involved in decision making by ancient peoples. Rather, the desired product is one with which archaeologists are able to accurately illustrate our current understanding of places of importance in the region's human history. This product will then be integrated with complementary efforts by ethnographers and historians, natural scientists representing ecological interests, and current land and business owners in the area. This combination of views is necessary to fill out our understanding of the landscape and its value. We must then communicate our results effectively to a wide audience, including policy makers and the public.

To effectively accomplish these goals we must be applied anthropologists, fully engaged with the community and mindful of our work in a larger context (Pyburn and Wilk 1995). One of our major challenges in this type of work is to identify sensitive locations, or that part of the archaeological record that faces imminent threat of conflict with other dynamic elements in the community. Furthermore, the model we develop must be recognized as a single step in an evolving process for which many future models will be required to address the constantly changing nature of the present as articulation of past and future.

Study Area

Santa Cruz County is located in southeastern Arizona adjacent to the U.S.-Mexico border (Figure 1). It comprises an area of approximately 3200 km^2 of Basin and Range topography with elevation ranging from 900 m asl to 2880 m asl. The dominant geographic feature in the region is the Santa Cruz River, which begins in Arizona, flows into Sonora, Mexico, and then curves west and north to re-enter Arizona and flow toward its confluence with the Gila River in south-central Arizona. The other dominant geographic features of the area are the Santa

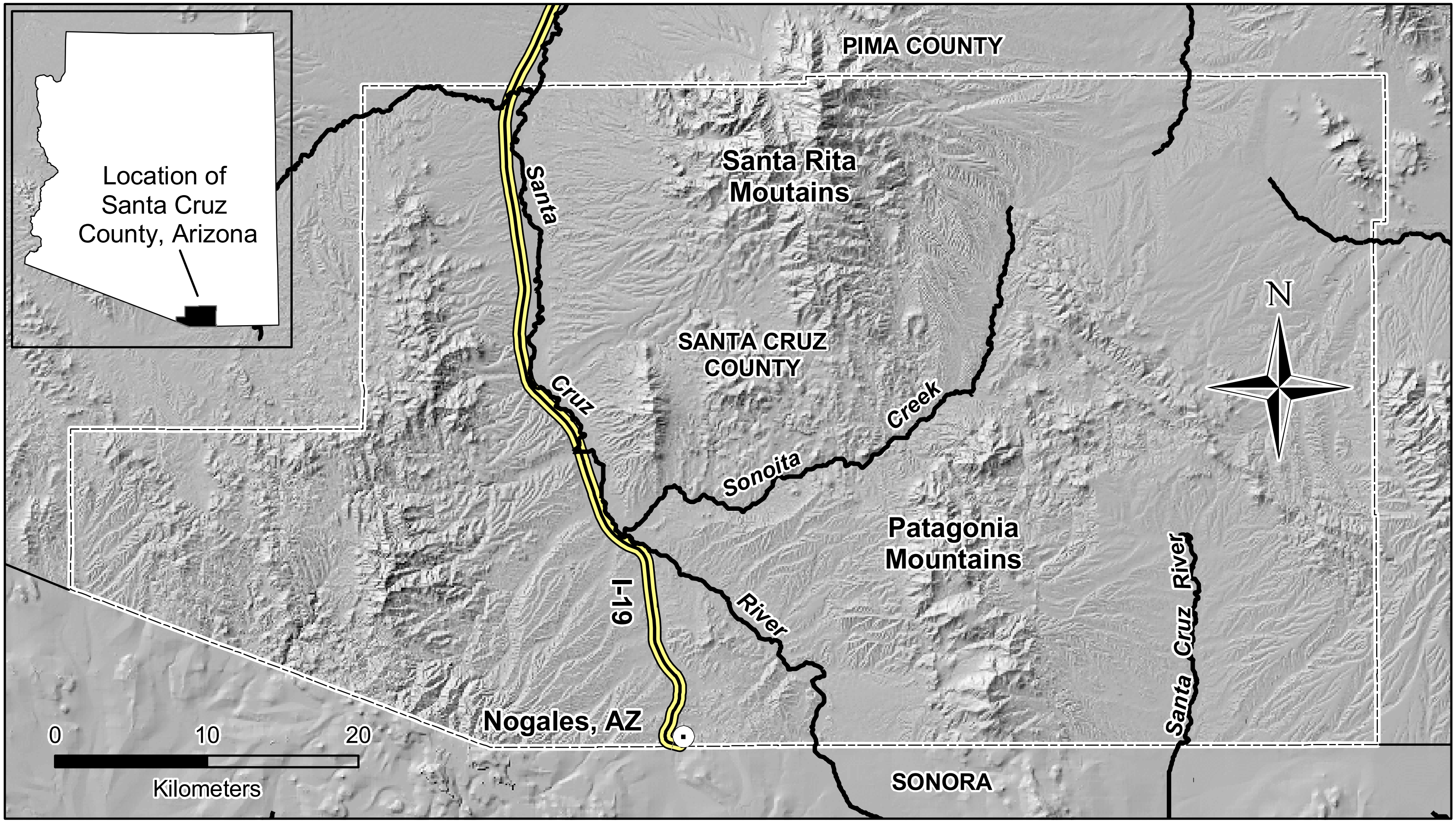

Figure 1. General Map of Santa Cruz County Study Area.

Rita and Patagonia Mountains that flank the river valley and contribute a large portion of its flow. The region is dominated by Sonoran and Chihuahuan Desert vegetation, except in the mountain elevations where Madrean evergreen woodland contains relict Pleistocene flora and fauna typical of cooler and wetter climates (Brown 1994; Deaver and Van West 2001). Annual precipitation in the area ranges from 300 mm in the low desert to 900 mm in the higher elevations.

Culturally the area has been the location of human habitation since the early stages of New World occupation over 12 kya, and several Paleo-Indian sites are recorded here. It is also the location of Archaic and Early Agricultural Period sites, and an ideal riverine setting for the introduction of domesticates to the region approximately 3.5-4 kya (MacWillams 2001). During the last centuries before European contact what is now Santa Cruz County was on the border between the Hohokam and Trincheras culture areas. When the first European explorers arrived the area was occupied by Piman groups, whose descendents still live here. Overall there is good evidence that some parts of the area were occupied fairly consistently for several thousand years, and many areas of occupation in earlier times are still the primary loci of occupation today.

Analytical Techniques

Over the last two decades of research using GIS and statistical approaches to settlement analysis, several techniques for model development have been described in the archaeological literature. The dominant form of model to emerge from this literature is one in which attributes of the environmental context of archaeological sites are subjected to statistical analyses evaluating correlation among variables. One popular and robust statistical technique is logistic regression (Kvamme 1983; Parker 1985; Warren 1990b), which has proven to be a powerful and easily interpreted method when appropriate data are available. Advantages of logistic regression include fewer assumptions about the distribution of independent variables, and output ranging from 0-1 that can be interpreted as a probability. Furthermore, logistic regression is suitable for use with binary dependent variables and a range of independent types, including categorical variables common in environmental studies.

The logistic regression method in predictive modeling emphasizes the attributes of land parcels rather than sites and produces a probability surface reflecting the likelihood of a given parcel being a desirable location for past land use. This emphasis on land parcels makes possible binary description of the dependent variable as site vs. non-site. Many descriptions of logistic regression and its strengths are available in the literature and several examples of its use have been published (e.g. Kvamme 1985; Carmichael 1990; Duncan and Beckman 2000; Warren and Asch 2000).

Archaeological Data

Information on site locations and survey projects in Santa Cruz County was obtained from AZSITE and the Arizona State Museum (ASM). We focused on pre-European contact period sites because a separate effort was under way to identify historic properties and it was unnecessary and probably inadvisable to model their locations (Kvamme 1988a). We narrowed our scope to habitation sites because these are likely to represent the broadest range of activities relevant to the stated interpretive themes, and they reduce the necessity to identify numerous site functional types with survey data. The identification of habitation sites was typically a judgment call based on the original recorders' interpretation or on criteria identified in the site description. This process resulted in a set of 160 pre-contact, habitation sites deemed to be most representative of past land use and of cultural resources needing protection.

For non-site locations we used archaeological survey polygons obtained from the AZSITE database comprising 148 projects covering over 70.58 km^2 and representing approximately 2 percent of the area of Santa Cruz County (See Figure 2 for locations of sites and survey areas). A non-site was defined as any area where survey did not reveal the presence of archaeological resources. To

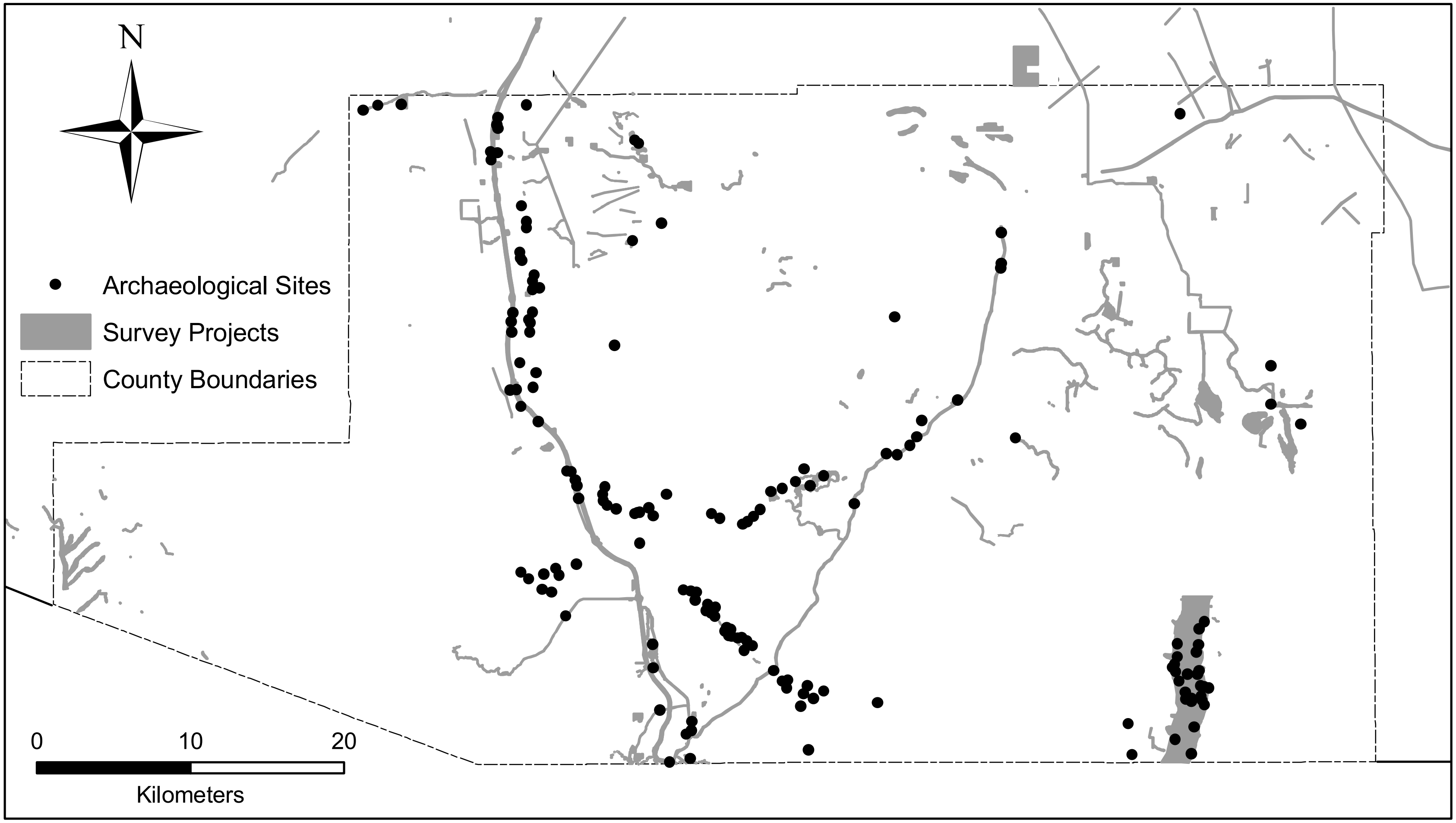

Figure 2. Map Showing Locations of Archaeological Sites and Survey Projects used in Model.

address concerns about the actual range of activities around sites, and to increase differences among site and non-site attributes, 3 km buffers were constructed around all site locations. Areas inside this distance were removed from consideration as non-site locations. The concept of site location and boundary is problematic in archaeological predictive modeling (Ebert and Kohler 1988; Ebert 2000). Nonetheless, the logistic regression method and a binary response variable necessitate such an approach.

Limiting non-site locations to those areas over 3 km from confirmed sites helps alleviate uncertainty about the actual range of site activities that may structure concentrations of material remains. This distance represents a minimum distance used by settled agriculturalists in their pursuit of most resource extraction and represents a cutoff between activities associated with a habitation site and areas not perceived as attractive for such activities. Non-site areas were converted to point locations at 200 m grid spacing to create a set of data with attribute association comparable to site locations. This process resulted in the identification of 310 non-site locations distributed broadly across Santa Cruz County.

The use of data such as these in a statistical model poses problems of interpretation because they are biased and do not represent a random sample. This is a common problem for researchers attempting to use existing data and efforts to compensate for such bias have been explored (Kvamme 1988b; Massagrande 1995). The importance of having a random sample is to provide a representative set of locations for statistical analysis, and the common view would be that a biased sample would provide biased results. It is necessary, however, to consider more closely the question of bias and representativeness in this case. For many purposes it would be desirable to have a sample of locations that was representative of the full range of past land use. The use of unrepresentative data in model development would risk missing important and unknown aspects of behavior. Some have argued that it is precisely these unknown elements that are most important because they provide the most new information (Altschul 1988, 1990). For the current project, however, this poses less of a problem and existing bias may, in fact, be used to advantage.

The importance of a representative sample rests on an assumption that it is past land use we desire to explain. However, if our goal is to model the articulation of past land use with current and future land use, the existing sample may be appropriate for our needs. While it is not a random sample, it is representative of recent and contemporary interest in the landscape from a development point of view. The distribution of known sites and modern archaeological surveys in this region are a good reflection of the range of interest it has received over the last several decades. The variable scrutiny received by different areas is an indication of how much activity has occurred and is likely to occur in the near future.

The goal of producing a sensitivity map suggests a desire to identify cultural resources that are subject to imminent effect by development, and modeling sensitivity requires consideration of both the resources and development trends. Bias inherent in much existing archaeological data produced by CRM may essentially be considered a weighting factor for threat level. Rather than apply techniques to correct for this bias, we chose to use it strategically, emphasizing those areas most likely to be impacted by developments in the near future.

Environmental Data

Obtaining and developing useful environmental data can be the most time consuming and costly aspect of a predictive modeling project. While some projects are able to include collection of environmental data in conjunction with archaeological survey, our project constraints did not allow for such an integrated approach. Rather, we were forced to use available data that was typically collected for quite different purposes and recorded at a scale that may be inappropriate for use in modeling some aspects of prehistoric land use (Crumley and Marquardt 1990; Allen 2000). One of our principal needs was to derive meaningful attributes from these data and still discriminate useful variation among geographic attributes. Our study would generally fall into a regional classification, in which broad environmental characteristics such as soil, climate and vegetation are thought to structure settlement choices (Allen 2000).

The primary sources of digital environmental data for this region are the Arizona Land Resources Information System (ALRIS), and the United States Geological Survey (USGS), both of which provide free data for use in non-commercial applications (See Table 1 for description of data layers used). Slope and flow accumulation data were derived in *ArcGIS* from the DEM using the *Spatial Analysis* extension and the *ArcHydro* data model. These data were further developed using neighborhood statistics to more appropriately reflect qualities in the vicinity of sites that would affect their suitability. This approach utilizing neighborhood attributes more closely follows the goals of a landscape approach to modeling (Church et al. 2000). We calculated the neighborhood mean of elevation and slope within 200 m of site and non-site locations.

Table 1. Environmental Data Used in Models

Map Layer	Source	Scale	Origin	Comment
Vegetation	ALRIS	1:126,720	Brown and Lowe 1974	10 plant communities in Santa Cruz County
Springs	ALRIS	1:24,000	USGS Geonames database	171 spring locations in Santa Cruz County
Geology	ALRIS	1:1,000,000	Reynolds 1988	34 combinations of bedrock and surface characteristics in Santa Cruz County
Soils	USGS	1:250,000	National Resource Conservation Service (NRSC), State Soil Geographic Database (STATSGO)	48 soil units in Santa Cruz County
Terrain (DEM)	USGS	1:24,000	National Elevation Dataset (NED)	30m grid resolution

One especially important consideration in site location that is difficult to address with standard hydrography data is the availability of water. In the desert southwest, this was an important consideration for prehistoric settlers, and it is a particularly troublesome thing to identify with current data in a way that reflects actual availability. Standard hydrography data available from sources such as the USGS do not adequately indicate the subtle variation in water availability in the desert and do not address differences between current conditions and those in the past. Simple distinctions between perennial and ephemeral streams, or methods of identifying stream order do little to indicate the actual quantity and timing of water availability that are critical to human uses. Furthermore, a great deal of change in surface water availability has occurred over time, particularly in the last century as modern uses have affected flow characteristics and the water table.

In the present analysis, for example, only two small segments of the many streams in the area were identified as perennial with the rest considered ephemeral. It is well documented in the historic literature that there was a much more extensive perennial flow in the larger streams of this region (Castetter and Bell 1942; Dobyns 1981). In addition, the mean distance to any stream from sites used in these analyses was 294 m, compared to 303 m for non-site locations. A three percent difference in distance to ephemeral water sources hardly reflects its importance in this desert region and would provide minimal utility in discriminating among likely settlement locations. To best identify hydrologically useful locations would require a laborious paleoenvironmental study emphasizing geomorphological evidence of past fluvial conditions. In the absence of such a study, we focused on hydrological modeling as the best way to understand the relative availability of water to prehistoric settlers.

Hydrological modeling characterizes the direction and accumulation of flow based on terrain. The size of watershed is one of the most important qualities affecting the amount of water that flows in a given drainage. Based on the slope and aspect of each pixel in relation to its neighbors in the DEM, it is possible to calculate the total area that flows into each pixel, or its flow accumulation. Again, this is a quantity most usefully described as a neighborhood statistic, as sites were typically situated near, rather than in locations of high accumulation.

A neighborhood sum was used to indicate the total area of watershed contributing to hydrologic flow within 1 km of a site location. This measure characterizes the amount of flow available in close proximity to a settlement and reflects variable availability as the distance from sites to drainages increases. Furthermore it emphasizes the importance of locations at stream confluences that have been noted as persistent places (see Schlanger 1992). Stream confluences both increase the area of high flow potential within such a radius and reflect the importance of tributaries in raising water table levels and creating more regular flow. The calculation of the neighborhood statistic resulted in a mean flow accumulation in the vicinity of sites that is more than 127 times greater than the mean for non-site vicinities, and appears far more indicative of the variable availability of water and its relative importance in this environment. Because of the shape of the distribution of the accumulated flow variable, it was log transformed to produce a better correlation with site distribution.

Each of the environmental variables described above was then assigned to the collection of sites and non-sites by location to produce a table for statistical analysis. All are important qualities potentially affecting the choice of a location for settlement. Chi-square and Kolmogorov-Smirnov tests were used to evaluate correlations between each of these variables and the site/non-site distinction, and all were found significant at the 95 percent level. Examination of this list of variables, however, suggests that the factors that structure their geographic distribution are often overlapping and hence not completely independent. For example, the distribution of vegetation communities is closely related to terrain qualities including elevation and aspect. In truth, very little that is recorded as an environmental variable is independent of all other environmental variables. Much of what has structured human settlement patterns is inter-related in complex ways with multiple environmental qualities that make simple correlations impossible.

Statistical Techniques

An important consideration in any multivariate statistical model is which variables to include and different goals entail different considerations. One approach is to minimize the number of variables used for an explanatory model because too many variables may saturate or over-parameterize a model. Furthermore, as noted above, many environmental variables are not truly independent and, while their addition may produce high statistical correlations, it provides relatively little gain in explanatory value. Thus, some techniques seek to minimize the number of variables used in order to focus on those variables with the greatest explanatory power. Predictive models developed for management purposes, however, are not as constrained by explanatory needs, but rather strive for improved predictive efficiency to enhance planning. In such cases a larger number of variables may provide a better model because they increase the accuracy of predictions and focus on a smaller area, improving model efficiency.

A common technique used in regression models to select the most appropriate variables is stepwise selection, in which variables are added or removed from a model in steps based on a pre-established P value of significant model improvement. Stepwise regression, however, has come under criticism in recent years (Raftery 1995). One problem identified in archaeological applications is that different sets of variables may be indicated depending on the sample and stepwise procedure (Kvamme 1988a). Such difficulties are evident in the present analyses, in which different sets of variables are indicated for a randomly selected sample of 100 sites and 100 non-sites than for the complete sample. Furthermore, different sets are indicated for backward versus forward stepwise selection in both the random and the complete samples. Some aspects of model performance using different variable subsets indicated by stepwise procedures are evaluated below.

Because of dissatisfaction with stepwise procedures, sociologists have developed techniques relying on information criteria statistics that can aid model selection. In particular, Bayesian hypothesis testing with the use of the Bayesian Information Criteria (BIC) approximation (Schwarz 1978; Raftery 1995) has proven useful, especially in models using categorical data. The BIC approximation provides a useful means of evaluating and comparing the information value of competing models. The BIC approximation is calculated by Raftery (1995:134) as follows:

$$\text{BIC} = -\text{LRT} + p_k \log n$$

where LRT = Log Likelihood Ratio, p_k = number of degrees of freedom (or independent variables), and n = number of cases.

The most negative BIC indicates the best model choice. Other information criteria approximations may also provide useful results and can be used with stepwise procedures for models with large numbers of independent variables resulting in overwhelming combination possibilities (Shtatland et al. 2001). For present purposes a modest number of independent variables were available and we used the BIC evaluation.

The final critical aspect of these analyses is assessing the performance of different models. A useful and simple technique for evaluating model performance is the gain statistic presented by Kvamme (1988a:329) and defined as:

Gain = 1 - (percentage of total area covered by model/percentage of total sites within model area)

Model utility is scaled from low to high on a scale of 0 to 1.

This statistic provides a sense of the efficiency of prediction as a function of area and is useful for comparing models developed using different techniques. For example, one model may correctly predict more sites than another, but at the expense of including greater area, and hence is not more efficient.

Another key to assessing model performance entails the establishment of a cutpoint. The logistic regression statistic is scaled continuously from 0 to 1 and it is necessary to establish a point along that continuum at which a value is considered a positive or negative prediction. The most straightforward cutpoint establishes any value above .5 as a positive prediction and any value below as negative. This approach, however, does not address distinctions between wasteful and gross errors (Altschul 1988). Wasteful errors result from inefficient models and incorrectly identify areas of high probability. Gross errors result from failure to identify high probability locations and are considered a greater problem, as they may result in the destruction of important cultural resources. For this reason selection of cutpoint probabilities that optimize desired predictions may be preferable. For example, in a management/preservation context we may desire a model that accurately predicts at least 90 percent of site locations.

Model evaluation also presents important problems with regard to data sampling. To avoid wasting valuable information the best possible model that can be developed typically uses all site and non-site points (Kvamme 1988a). Ideally a second set of independent data would be produced with which to evaluate model performance. In the present case, and in most CRM contexts, it is not feasible to produce a second set of independent data for evaluation within a useful time frame. Alternatives include testing with the same data used to build the model, and splitting the sample, with one subset used for development and the second for evaluation. In the first case, evaluations of performance are often overly optimistic and do not reflect actual predictive power with independent data. In the second case, splitting the sample diminishes the performance of the model because not all information is used. This is particularly problematic with small data sets. Different approaches were used here and their relative merits will be discussed further below.

Results and Discussion

In this section we present results using different variables as indicated by stepwise versus BIC procedures, and using complete versus split samples. To begin, we focus on results using the complete data set but different subsets of independent variables. Using the BIC approximation to determine the best model, a combination including: flow accumulation, elevation, distance to springs, soils, and vegetation was found to have the best score of -476.

In contrast, the stepwise regression technique resulted in different variable selection depending on whether a forward or backward step was used. For the forward step with a P value of .05 to enter, flow accumulation, geology and soils were indicated. For comparative purposes this combination resulted in a BIC score of –430. For a backward stepwise approach only flow accumulation and elevation were indicated, resulting in a BIC score of -468.

The stepwise procedure is problematic in that two different sets of variables were selected depending on the procedure, making it difficult to ascertain which one might be the preferred choice. Moreover, neither set indicated by the stepwise technique provided the optimal BIC score. The variables indicated for the BIC model not only provide greater predictive power but seem more intuitively useful as well. Both soils and vegetation seem to be important qualities to settlers in this area and thus are logical to include in a model. In contrast, the geological distinctions provided by these data seem less likely to have been an important factor and hence seem inappropriate to displace soils and vegetation in our model.

Our forward stepwise model performed poorly and this method is thought to be an inferior choice (Shtatland et al. 2001), and thus is not discussed further. Here we compare the results of the BIC model and the backward stepwise model. Applying the regression formula to selected variables, and adjusting the constant for different sample sizes (Warren 1990), produced probability maps illustrated in Figures 3 and 4.

With the BIC model mean probability estimates for site locations are .97 and for non-site locations are .03, indicating generally strong discrimination between location types. The stepwise model produced a mean probability of .87 for site locations and 0.07, which is not quite as strong but still respectable. Using a .5 cutpoint probability the BIC model correctly predicted 98 percent of the sites and 98 percent of the non-site, whereas the stepwise model correctly predicted 90 percent of sites and 97 percent of the non-sites.

Examining frequencies of correct predictions at different cutpoint probabilities further illustrates some of the differences between the two models.

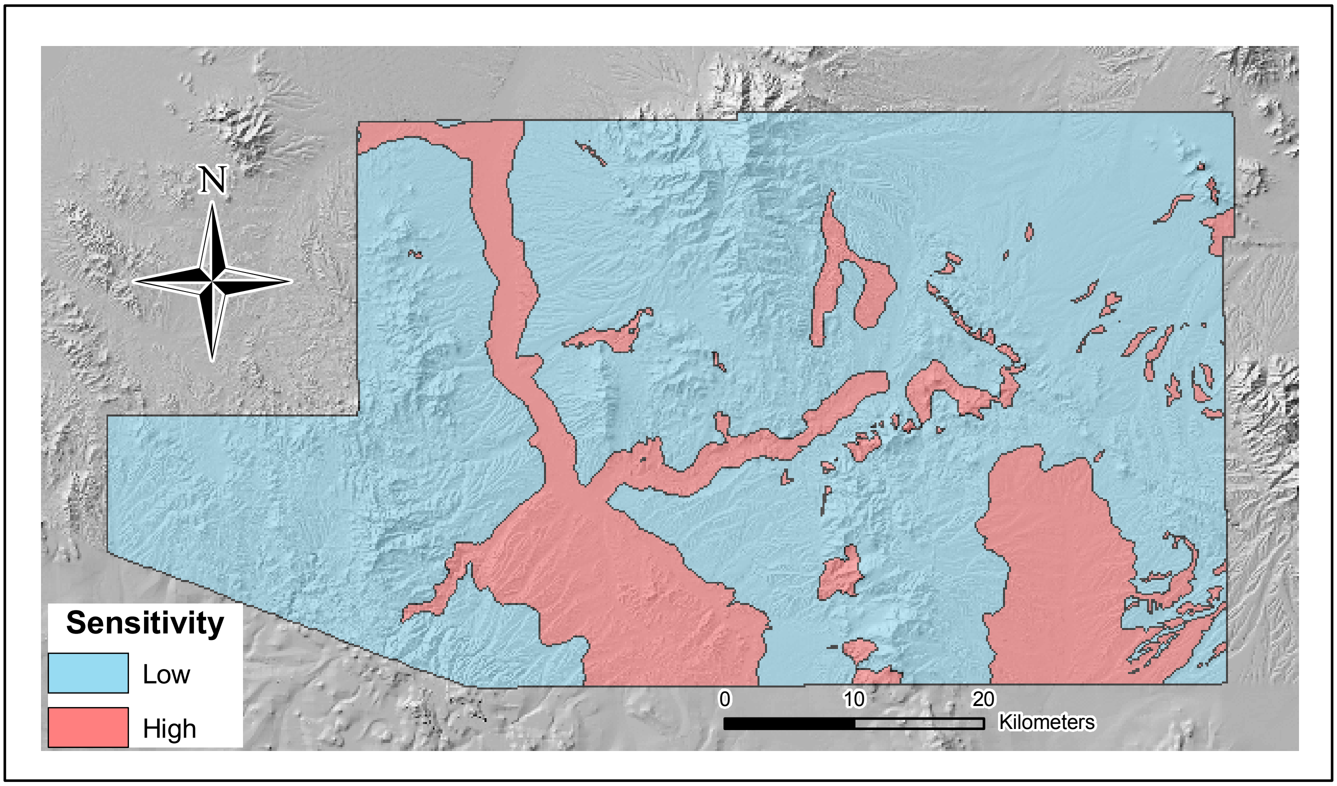

Figure 3. Map of BIC Approximation Model Correctly Predicting 90 Percent of Known Sites.

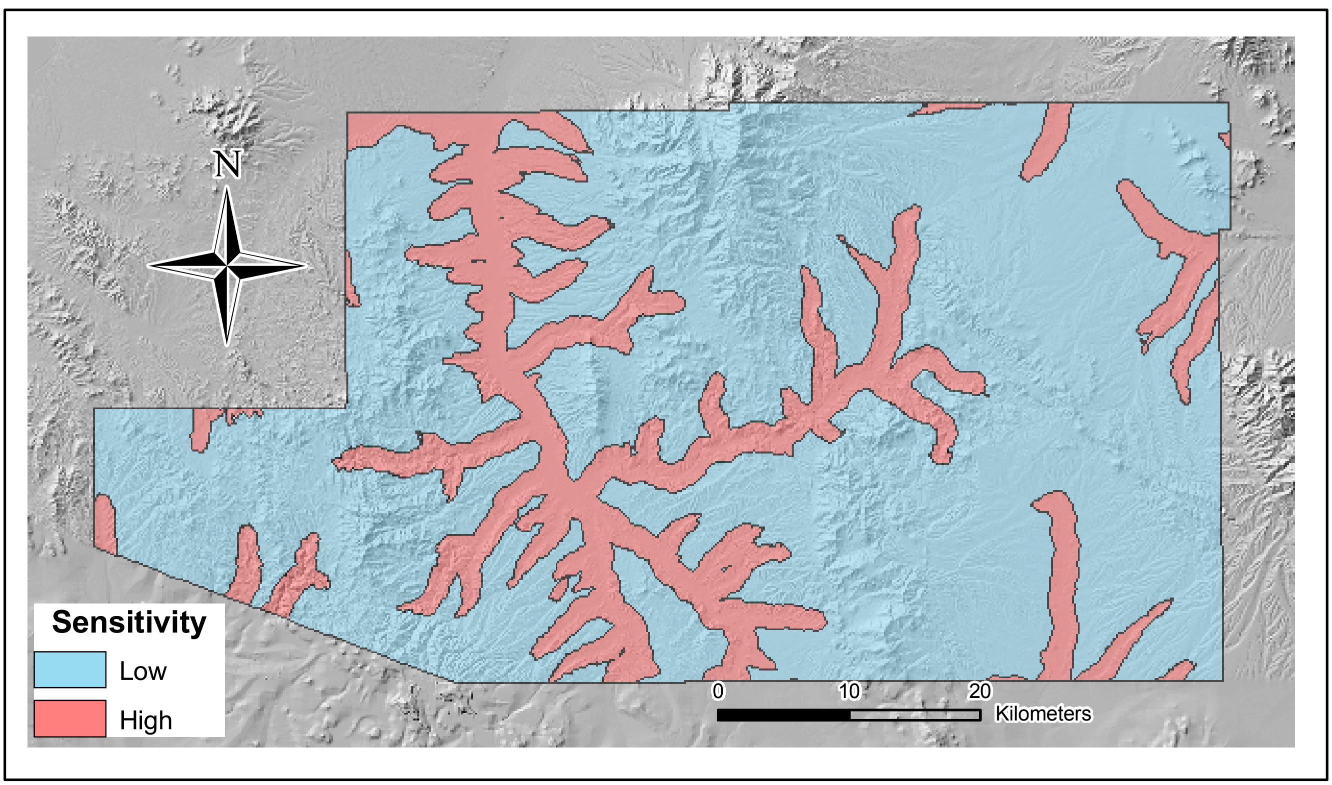

Figure 4. Map of Backward Stepwise Model Correctly Predicting 90 Percent of Known Sites.

To correctly predict at least 90 percent of the site locations, a cutpoint probability of .96 is required with the BIC model, indicating any location with a value below .96 as a negative prediction and any value above as positive. A more conservative cutpoint of .40 is required with the stepwise model. Using a .96 cutpoint in the BIC model still correctly predicts 100 percent of the non-sites, while the .40 cutpoint in the stepwise model correctly predicts 95 percent of non-sites.

Reclassifying the probability surface in the GIS to reflect negative or positive prediction based on these cutpoint values provides a means of calculating the gain statistic suggested by Kvamme (1988a). The area designated positive by the BIC model is 21.4 percent of the total, while the positive area in the stepwise model is 22.4 percent, providing gains of 76 percent and 75 percent respectively. While the gain provided by the two models is essentially the same, the BIC model appears to perform slightly better especially at minimizing wasteful errors while achieving a desired predictive power. In addition, the BIC model more accurately characterizes the importance of the Santa Cruz River valley where most land use, both ancient and modern, seems to be concentrated. For example, the emphasis apparent particularly in the upper reaches of the Santa Cruz Valley corresponds well with findings of other researchers documenting biodiversity and other indices of natural resource wealth (Center for Desert Archaeology 2004). This emphasis in the model is driven by recent focus on this area and illustrates the connections between current interest and archaeological sensitivity.

As a final element of our analysis we present the BIC model based on a split random sample of 100 sites and 100 non-sites, leaving a portion of the data for independent model evaluation. As noted above, the same five variables received the best BIC score using the random sample as with the complete sample. To correctly predict at least 90 percent of site locations a cutpoint of .94 is required, resulting in a positive area of 39 percent and a gain statistic of 59 percent. This is a decrease from the 76 percent indicated with the full data set, but still represents a substantial gain.

The question remains which model to use for our current purpose of defining archaeologically sensitive areas of Santa Cruz County for planning and implementing a National Heritage Area designation. While the model based on a smaller random sample allows for better evaluation of performance we prefer the model based on the complete data set. The same subset of variables is used in both models, supporting concordant inferences that hydrology, elevation, soils and vegetation were important environmental qualities structuring land use. In addition, both models appear to have a quite similar distribution across the landscape, again supporting a concordant view of the importance of the Santa Cruz River valley in the settlement of this area. However, the larger dataset utilizes significantly more information and provides a more efficient model focusing on only 21 percent of the area as opposed to 39 percent for the smaller dataset. It might be argued that the full dataset is overly particular, fitting the model to idiosyncrasies of the data, and hence is not as generalizable. In the present context, though, it is precisely the particulars of this area that are our focus in nominating the area for NHA designation. The general explanatory value of the model is shifted from why people did things the way they did in the past, to how a landscape that was important to them is still important to people living here today. Consequently, a model that more exactly represents how past land use in this place articulates with present land use is desirable.

Despite our current need to settle on a particular model illustrating this articulation, it is essential to consider modeling as an ongoing, iterative process. First, our current project is only a feasibility study and will be followed by continued effort as the NHA designation advances. Ultimately, much more detailed management plans may require more elaborate modeling efforts and consideration of new variables as we strive to clarify our understanding of more particular problems and relationships. Second, our understanding of the archaeology of this region is certain to improve dramatically as more research is conducted in coming years. Development is certain to expand greatly in the area, changing the articulation of past and present interests. The present model cannot be considered a final word on archaeological sensitivity in Santa Cruz County. Rather we hope that our efforts and the lessons learned will serve as a productive foundation for continued work. We are encouraged that this initial project has offered a useful model and numerous valuable insights into the modeling process.

Conclusions

Predictive modeling has long held promise as a powerful tool to help archaeologists understand patterns of land use. Technological improvements in methodology, computing power and data access now make useful modeling a practical goal for many in our field. In the project described here we were able to use readily available data and technology to produce a model offering significant insight into the ways in which the landscape of southeastern Arizona articulates past and contemporary land use. We are able to produce a map depicting those areas in Santa Cruz County most susceptible to the conflicting goals of preserving and highlighting our unique past, and future economic development. For this we are indebted to a generation of archaeologists who have developed techniques and raised important questions about predictive modeling. At the same time, we encountered new challenges and solutions to problems many in our field may find useful. We hope the present discussion offers some value in three areas of predictive modeling in archaeology.

First, the matter of water availability is a critical factor in many parts of the world and tools for hydrological modeling in GIS offer valuable methods for more accurately assessing the variable availability of water across a landscape. We used a fairly simple approach quantifying accumulated flow with good success. This approach can be improved in the future with more complex modeling of variable precipitation and geology in different drainages that also affect the amount of surface water available.

Second, the matter of archaeological data for model development is problematic particularly for small projects with limiting financial and schedule constraints. In many areas abundant archaeological data may be available that has been perceived as unsuitably biased for modeling purposes. While others offer useful suggestions for addressing bias in archaeological data, we argue that in some CRM contexts this bias may be turned to advantage as a weighting factor emphasizing contemporary threats to cultural resources. The bias in existing data may thus offer a useful measure of threat sensitivity that is important in managing and preserving these resources.

Finally, selection of appropriate variables has been a challenging aspect of model development that has been unsatisfactorily met through stepwise techniques. Methods such as the Bayesian Information Criterion approximation offer useful ways to assess the utility of variables for inclusion. The BIC approximation avoided problems of forward versus backward stepwise procedures, and of using different samples of the dataset. Models indicated by the BIC appeared to provide as good or better predictive power and gain than models indicated by the stepwise procedure, and were intuitively more satisfying.

In preservation archaeology the goal of predictive modeling is no longer simply explaining past behavior but how that behavior influences the present and takes on contemporary economic, political and ideological value. Substantial amounts of money and effort are currently devoted to the preservation and recognition of cultural resources in the U.S. and many other countries. If this trend is any indication of value as perceived by society, then diverse approaches to predictive modeling that offer efficient and timely maps of past land use become important elements in our view of the historical landscape. The current project was initiated as part of a larger heritage tourism and preservation effort and requires a focus on the ways that past land use are integrated with current land use, and to an increasing degree will structure future land use. It is, in fact, the express purpose of this effort to create a model of the landscape as a product of the past to structure the future. This is not a model of the past to simply inform us, but an active effort to shape the future in a particular way.

Debates about predictive modeling in archaeology often revolve around whether environmental projection in the absence of deeper explanation is a valid endeavor. This debate is typically framed by an assumption that explanation is the only valid goal and therefore models that do not adequately accomplish this goal simply mask our ignorance. We argue that this assumption misses a separate but important goal. Archaeologists are not simply in the business of explaining why people did what they did in the past, and we do not here pretend to offer new knowledge on this subject. Instead we argue that part of our job as archaeologists is to inform a public interested in balancing preservation and development about where these goals interact and conflict with one another. To answer "What are we learning that we didn't already know?" we do not simply need to explain the past better, but rather to explain where the past will impact, and be impacted by a future we predict will still care.

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